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Research Article

Investigations on Severity Level for Diabetic Maculopathy Based on the Location of Lesions

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ABSTRACT

Computerized recognition of lesions in retinal images can support the early diagnosis and screening of a common disease, diabetic maculopathy (DM). A computationally well-organized tactic for the localization of lesions in a fundus retinal image is offered in this paper. DM is an ophthalmic system disease initiated by complication of diabetes. It is a foremost source of blindness in both middle and advanced age groups. Former recognition of DM defends patient from vision loss. Feature abstraction techniques can shrink the effort of ophthalmologists and are used to gladly perceive the endurance of aberrations in the retinal images assimilated during the screenings. Lesions are a foremost source of DM. In this paper, the lesions are perceived by means of the Fuzzy C-means clustering algorithm in the nondilated retinal images. The developed system consists of image acquisition, image preprocessing with a combination of fuzzy techniques, feature extraction, and image classification. The fuzzy-based image processing decision support system will assist the diabetic retinopathy screening and reduce the burden borne by the screening team. Feature abstraction dramas an energetic protagonist in perceiving the diseases and also it concentrates on ruling the brutality of disease through cascade neural network classifier and fuzzy classifier.

Key words:
Cascade neural network classifier, Feature extraction, Fuzzy C-means algorithm, Fuzzy classifier, Lesions

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INTRODUCTION

In medical solicitations, computerized retinal image investigation completed the detection of retina pathologies much easier for ophthalmologists; whereas predictable methods, such as dilating the eye pupil, gross time, and make patients agonize for a while. Diabetic maculopathy (DM) is the name given to the changes in the macula of the diabetic patients. It is nourished by a network of blood vessels, and any modification in these blood vessels can origin the snags with vision. The walls of the blood vessels become inelastic, dripping blood, and protein around them. Uncertainty the amount of blood which leaks out is fairly small, and the only symptoms might be a few areas of blurring or floating spots in front of the eyes,[1] This is called microaneurysms. Later, the blood vessels may stop carrying blood eternally, and the cells in the macula will die from lack of nourishment. This kind of loss of sight is permanent. The proteins and lipids getting leaked from the bloodstream to the macula through damaged blood vessels are the chief cause of lesions. The hard lesions are formations of lipid that are leaking from the weakened blood vessels. As the retinopathy progresses, the blood vessels become blocked which produce microinfarcts in the retina.[2,3] These microinfarcts are known as soft lesions. If the lesions extend into the macular area, vision loss can occur. When old blood vessels close down, new but abnormal ones will rise to occupy their place. They are not having the ability to nourish The retina appropriately and may rise to the transparent Inner part of the eye, and further affect the vision.[4] Retinal images obtained by the fundus camera are used to diagnose DM. Automated methods of DM screening help save time, cost, and vision of patients compared to the manual methods of diagnosis.[5,6] The screening of diabetic patients for the development of DM can potentially reduce the risk of blindness in these patients by 70%. Many methods are proposed for the detection of lesions. The nondilated low contrast fundus image is shown in Figure 1.

Sopharak *et al.*[7] applied the Fuzzy C-means (FCM) algorithm to detect the lesions. In Phillips *et al.*,[8] a thresholding technique based on the selection of regions to detect the lesions was applied. Soft lesions were detected using global thresholding, and the hard lesions are detected by local thresholding. In Wang *et al.*,[9] color features on a Bayesian statistical classifier used to classify each pixel into lesion or nonlesion classes. Usher *et al.*[10] describes the development of an automated system to detect abnormalities such as microaneurysm, hemorrhages, and lesions in color retinal images. They performed contrast enhancement, segmentation to reveal lesions followed by classification of lesions using a neural network. Jaykumari *et al.*[11] discusses the novel technique of intelligent segmentation followed by classification of lesions by using Echo State Neural Network (ESNN). Moving Window is used to obtain the statistical feature of the images, which are fed as input to ESNN. Further Osareh *et al.* has also compared the performance of NN for lesions detection with SVM,[12] and three other classifiers as follows: Linear delta rule, K-nearest neighbors (KNN), and quadratic Gaussian classifier.[13] KNN performs best among all the above three classifiers. More than the KNN performance, cascade neural network (CNN) performs well because it has no backpropagation.

In this paper, a computerized algorithm for the recognition of DM using FCM and CNN is offered. Nondilated low-contrast fundus images are segmented using FCM clustering;[14] then, segmented regions are categorized into two separate classes – normal and abnormal clusters using a fast and independent training algorithm called cascaded neural network and fuzzy. This includes retinal image acquisition, preprocessing, gray-level co-occurrence matrix (GLCM) feature extraction, FCM algorithm, and CNN.

METHODOLOGY

The proposed automatic screening methodology is shown in Figure 2. It starts with image acquisition, preprocessing, and then FCM segmentation is applied to the preprocessed images to identify the lesions. Then, the segmented image is assessed for the degree of abnormality of an image as normal or abnormal using CNN and fuzzy classifier.

Retinal Image Acquisition

The detection of lesions is done by an automated screening system; it requires nonmydriatic digital fundus photographs as input which is captured by nonmydriatic retinal cameras. In this project, 50 digital fundus images collected from the STARE databases are used.

Image Enhancement

Image enhancement is used to improve the quality of the original image which is more suitable for the specific application. The preprocessing stage involves green channel extraction, noise removal, and histogram equalization which produces an enhanced image.

Green channel extraction

Green channel extraction is the process of converting the color image into the green channel image. Normally, an RGB color comprises red, green, and blue colors. The green channel abstraction crops high-contrast image. The green color plane was used in this analysis since it shows the best contrast between the vessels and the background.

Noise removal

Usually, it is necessary to perform a high degree of noise reduction in an image before the execution of higher-level processing steps. One of the nonlinear digital filtering techniques called median filter is used to eliminate noise from images. Its edge-conserving nature makes it useful in cases where edge blurring is undesirable. Median filtering operation trades a pixel by the median of all pixels in the neighborhood of small sliding window. It may be applied before segmentation to reduce the amount of noise. The median filter reduces the variance of the intensities in the image. It vagaries the intensity mean value of the image if the spatial noise distribution in the image is not even within the window. After applying the median filter, new gray values are not generated.

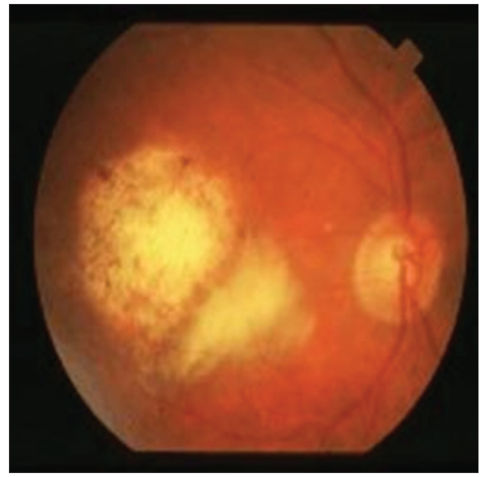

Figure 1: Nondilated low-contrast fundus image

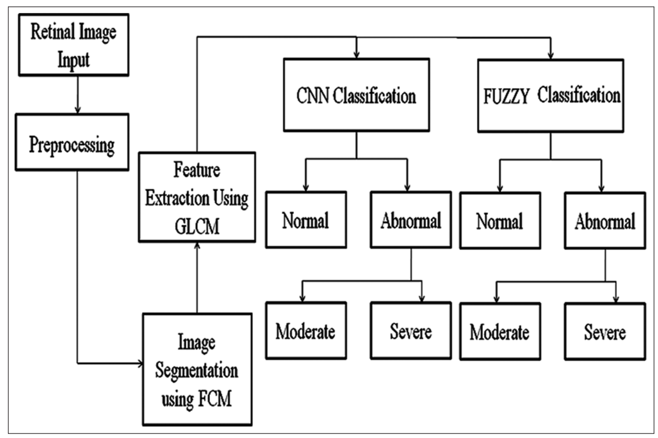

Figure 2: Flow diagram of the proposed method

Histogram equalization

Histogram equalization is a technique where the histogram of the resultant image is as flat as possible. Histogram equalization provides more visually pleasing results across a wider range of images. Contrast-limited adaptive histogram equalization (CLAHE) is a technique used to improve the local contrast of an image. It is a simplification of adaptive histogram equalization and ordinary histogram equalization. The CLAHE algorithm splits the images in the contextual region and applies the histogram equalization to each one. The result of the preprocessing step as shown in Figure 3 is applied to the FCM algorithm to detect the lesions.

Image segmentation

The image segmentation is a progression of segmenting the images into significant groups of connected pixels. While

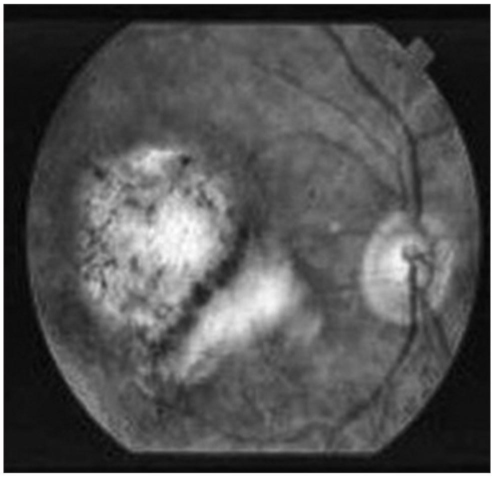

Figure 3: Illustration of the preprocessing on an image of the given image

processing at some point, a decision is ended about which image points or counties of the image are germane for auxiliary processing. Here, the segmentation is done by means of clustering of pixels and the algorithm used the FCM algorithm.

FCM

FCM is a data-clustering technique in which a dataset is composed as n clusters with every data point in the dataset fitting to every cluster to a convinced level. Segmentation using FCM clustering is an overlying clustering algorithm, where every point may belong to two or more clusters with different degrees of membership. The similarity is distinct by the distance of the feature vectors to the cluster centers. Euclidean distance is used to compute this distance and data will be associated to an appropriate membership value.[15,16]

Steps for FCM clustering algorithm:

1. Set the screen matrix U = [uij] (U (0)) by engendering random numbers in the range from 0–1subject to equation 5

$$C_j = \sum_{i=1}^{M} \sum_{j=1}^{C} u_{ij} = 1 \quad (1)$$

2. At k-step: Compute the centers vectors, c(k) = [cj] with U(k), by equation

$$C_j = \frac{\sum_{i=1}^{M} u_y^m x_i}{\sum_{i=1}^{M} u_y^m} \quad (2)$$

3. Updating the fuzzy partition matrix U(k), U(k+1) by the new computed uij according to the following equation

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{|x_{i\_}c_j|}{|x_i - c_k|} \right)} \quad (3)$$

4. Compute the objective function according to equation 1. If the variation between adjacent values of the objective functions is less than the termination criterion, then stop the iteration; otherwise, return to step 2.

$$l_m = \sum_{i=1}^{M} \sum_{j=1}^{C} u \left\| x_i - c_j \right\|^2 \quad (4)$$

Where, $1 \leq m < \infty$, u_{ij} is the degree of membership of x_i in the cluster j, x_i is the i^{th} d-dimensional measured data, c is the d-dimension center of cluster, ||*|| is any norm expressing the similarity between any measured data and center, m is an exponential weighting function that controls the fuzziness of the membership function, M is number of features, C is number of clusters.

5. Stop the iteration until

$$\max_{ij} \left\{ \left| u_{ij}^{(k+1)} - u_{ij}^{k} \right| \right\} \langle e \quad (5)$$

Where k is the iteration steps. This procedure congregates to a local minimum or a saddle point of J_m.

The output from FCM clustering is a list of cluster centers and n membership-grades for every pixel, where, n is a number of desired clusters of the pixel. A pixel will be assigned to the cluster with the highest membership-grade.

GLCM Feature Extraction

The identification of precise textures in an image is attained primarily by modeling texture as a two-dimensional gray-level alteration is called as GLCM.[17]

Using the GLCM matrix,[18] the following statistical features are extracted: Energy (ASM), Entropy (ENT), Correlation (COR), and Contrast (CON); where,

Energy

Energy dealings textural uniformity (i.e. pixel pairs repetitions). It is the square root of the angular second moment (ASM)).

$$ASM = \sum \sum P^2(ij) \quad (6)$$

Contrast (CON)

Contrast specifies the variance of the gray level.

$$CON = \sum \sum (i-i)^2 P(i,j) \quad (7)$$

Entropy (ENT)

This parameter measures the disorder of the image. Entropy is small, for texturall

y uniform image.

$$ENT = -\sum \sum P(i,j) \log[P(i,j)] \quad (8)$$

Correlation (COR)

$$COR = \left(\sum \sum ij \left(P(i-j) - u_x u_y \right) \right) / \sigma_x \sigma_y \quad (9)$$

Where P(i,j) is probability density, μ_x, μ_y, σ_x, and σ_y are mean and standard deviation of the sum of each row P_x and column P_y in the co-occurrence matrix.

Classification using CNN

Subsequently the recognition of lesions, the resultant image of the FCM algorithm is applied with the CNN algorithm. Among numerous classifiers or NN's, the CNN is the best architecture with no backpropagation. The ideas behind the cascade-correlation architecture are as follows:[19] The first is to build up the cascade architecture by adding new neurons together with their connections to all the inputs as well as to the previous hidden neurons. This configuration is not modified at the following layers. The second is to learn only the newly created neuron by fitting its weights so that to minimize the residual error of the network. The new neurons are summed to the network which increases its performance. Hence, the common cascade-correlation method assumes that all m variables X_1, …, X_m characterizing the training data are relevant to the classification problem. At the beginning, a cascade network with m inputs and one output neuron starts to learn without hidden neurons. The output neuron is linked to every input by weights W_1, …, W_m adjustable during learning. The output y of neurons in the network is given by the standard sigmoid function f as follows:

$$Y = f\left(X;W\right) = 1 / \left(1 + \exp(-W_o \sum_{i}^{M} W_i X_i)\right) \tag{10}$$

Where, $X = (X_1, \ldots, X_m)$ is a $m \times 1$ input vector, $W = (W_1, \ldots, W_m)$ is a $m \times 1$ weight vector, and W_0 is the bias term which is omitted. Then, the new neurons are added to the network one by one. Each new neuron is linked to all m inputs as well as to all the previous hidden neurons. Each time, only the output neuron is trained. Training a new neuron, the algorithm suitable for learning a single neuron can be used which adjusts its weights to reduce the residual error of the network. The algorithm sums and then trains the new neurons while the residual error decreases. The two advantages of CNN are as follows: no structure of the networks is predefined, that is the network is inevitably built up from the training data; the cascade network learns fast because each of its neurons is trained independently to each other [Figure 4].

A cascade network architecture consisting of neurons whose number of inputs, p is increased from one layer to the next layer. At the first layer, the neuron is linked to two inputs $X_{i1}, \ldots, X_{i2}$, $i1 \neq i2 \in (1, m)$. Let the input X_{i1} be an input for which a single-input neuron provides a minimal error. At the second layer, the new neuron is connected with the input X_{i1} as well as with the output of the previous neuron. The third input of this neuron can be linked with that input which provides a maximal decrease in the output error. Each neuron at the new layer can be connected in the same manner. More formally, the neuron at the r^{th} layer has $p = r + 1$ inputs. For a logistic activation function, the output Z_r of this neuron can be written as follows:

$$Z_r = f(U; W) = 1/(1 + \exp(-\Sigma i^p\, U_i W_i)) \tag{11}$$

Where, r is the number of layer, and U = (U1, …, Up) is a $p \times 1$ input vector of the r^{th} neuron.

As an example, Figure 5 depicts a cascade network for m = 4 inputs and r = 3 layers. The squares depict the synaptic links between the output neuron, two hidden neurons with outputs Z_1 and Z_2 and the inputs X_1–X_4.

After the detection of lesions, the classification is done using CNN classifier. CNN minimizes the empirical risk and prevents the overfitting problem which achieves good performance. By using the kernel function, CNN classifies the normal and abnormal images. The result of the CNN classifier is shown in Figure 6.

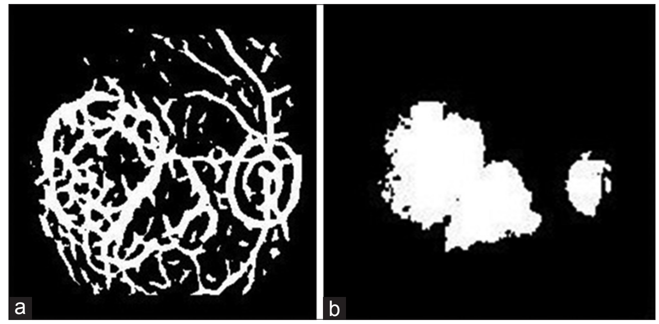

Figure 4: Result of Segmentation. (a) Blood vessel segmentation. (b) Lesions detected image using FCM

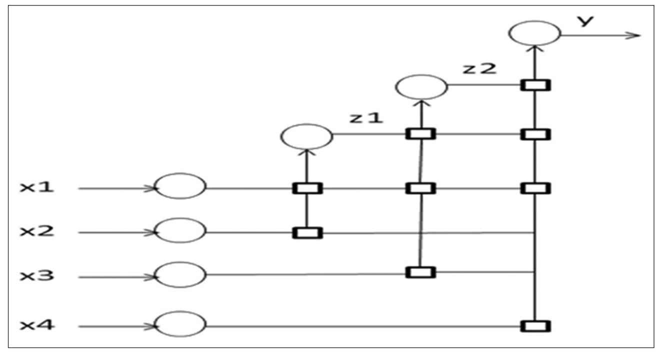

Figure 5: Cascade neural network for m=4

Classification using fuzzy

Grayscale conversion

The grayscale conversion, which converts the original color fundus images from the developed dataset to a grayscale image, is the first preprocessing technique used. The rgb2gray function is used to convert the color image into the grayscale intensity image by eliminating the hue and saturation information while retaining the luminance [Figure 7].

Fuzzy edge detection

An edge-detection method sometimes produces small intensity differences between two neighboring pixels which do not always represent an edge or which might represent a shading effect. Therefore, the use of membership functions Would overcome such problems by defining the degree Which a pixel belongs to an edge or a uniform region. A fuzzy inference system (FIS) using a Mamdani-type system is proposed here for edge detection. The image gradients along the x-axis and y-axis of the image are the inputs for the FIS. For each input, a zero-mean Gaussian membership function is specified, where if the gradient value for a pixel is 0 (region), then it belongs to the zero membership function with a degree of 1. Another membership function is added which specifies the standard deviation for the zero membership function for the gradient inputs. For the output, which is the intensity of the edge-detected image, a triangular membership function is specified. Next, the two FIS rules are added to make a pixel white if it belongs to a uniform region where both inputs are zero or otherwise the black pixel is presented if one of the inputs is not zero. To calculate the white pixels from the edge-detected image, the output image is converted or inversed into produces the black and white images. Figure 8 shows the

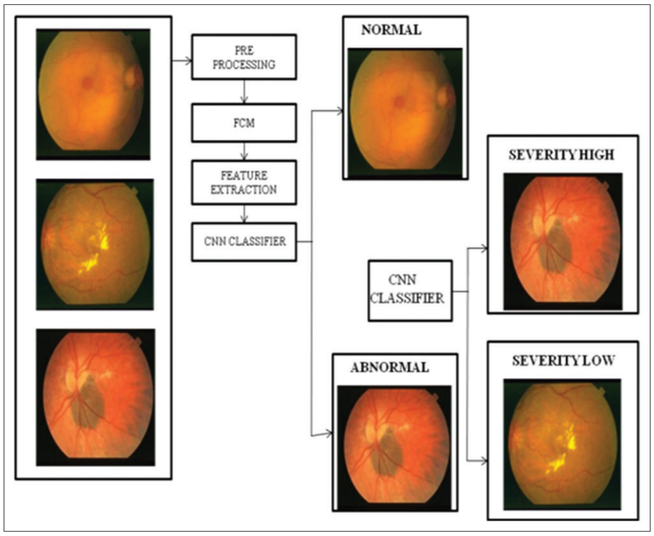

Figure 6: Result of cascade neural network classifier

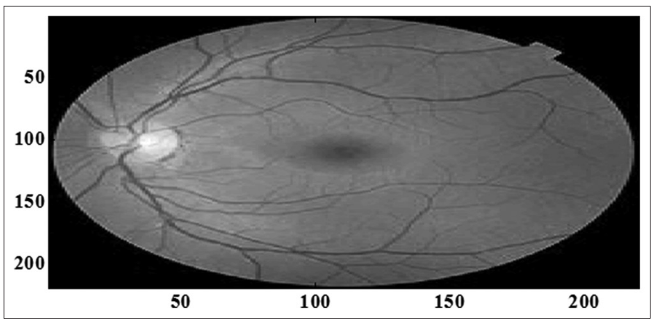

Figure 7: Grayscale conversion

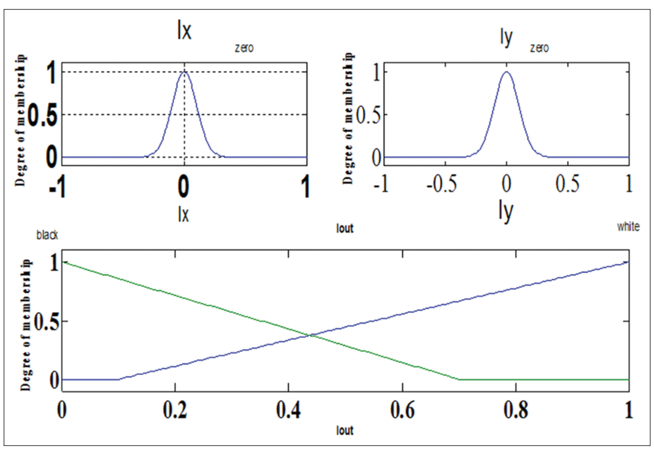

Figure 8: Membership functions of the inputs and outputs for the edge detection

membership functions of the inputs and outputs for the edge detection.

It shows the input classification of data is verified with normal and abnormal comparison fuzzy classifications of accuracy and sensitivity. The normal and abnormal are compared in this data set with the fuzzy. After the detection of lesions, the classification is done using fuzzy. Fuzzy minimizes the empirical risk and prevents the overfitting problem which achieves good performance. By using the kernel function, fuzzy classifies the normal and abnormal images.

Table 1: Severity levels

Severity level	Condition
20–50%	Low
50–60%	Moderate
60–90%	Severe

Performance Measure

The performance of the proposed system was evaluated using specificity, sensitivity, and accuracy.

Specificity

Specificity measures the proportion of negatives which are corrected identified as such (e.g., The percentage of normal healthy people who are correctly identified as not having the condition, sometimes called the true negative rate):

Specificity=TN/(TN+FP).

TN: True negative, FP: False positive

Sensitivity

Sensitivity also called the true positive rate. It measures the proportion of actual positives which are correctly identified as such (e.g., The percentage of exudates people who are correctly identified as having the condition)

Sensitivity=TP/(TP+FN)

Accuracy

Accuracy is the proportion of true results either true positive or true negative in a population. It measures the degree of veracity of a diagnostic test on a condition.

Accuracy=(TN+TP)/(TN+TP+FN+FP)

RESULT AND DISCUSSION

The digital fundus images collected from the STARE database are preprocessed in this work. The main aim is to deduct the lesions. The images are segmented, and the blood vessels are divided from the lesions. As we have used the CNN classifier is used for severity measurement, which is found to be more accurate, and the feature can be extracted.

Table 1 shows the average severity level of the eye image and the lesions conditions of the eye, the nondiluted low-contrast retinal digital images, and the neural network classifier is used in this work and found the sensitivity level.

Table 2 shows the nondilated retinal fundus input images were collected from STARE database. A database set of 200 retinal input images of which 70 normal and the remaining 130 abnormal images were collected from STARE database for testing the algorithm.

Table 3 shows the nondilated retinal fundus input images were collected from STARE database. A database set of 200 retinal input images of which 70 normal and the remaining

130 abnormal images were collected from STARE database for testing the algorithm.

In this method, the classification of data is verified with Normal and abnormal comparisons, fuzzy and CNN with the Classification of accuracy, specificity, and sensitivity. From the data 200, the normal and abnormal are compared in this dataset with the fuzzy and CNN classifier. The proposed algorithm CNN and fuzzy classifier are used for severity measurement. By using the extracted features, CNN classified the segmented image as the normal and abnormal and further the severity level of the abnormal image was classified as either high or low.

Table 4 shows the accuracy, sensitivity, and specificity for different fundus images STARE dataset, the various methods are used to classify the data. From the data are used, and 10 data are tabulated. The normal and abnormal are compared in this dataset. The proposed algorithm CNN classifier is used for severity measurement. By using the extracted features, CNN classified the segmented image as the normal and abnormal and further the severity level of the abnormal image was classified as either high or low.

Table 2: STARE database CNN classifier

CNN classifier	TP	TN	FP	FN
Normal	24	30	10	6
Moderate	30	20	10	10
Severe	30	20	6	4

TN: True negative, FP: False positive, TP: True positive, FN: False negative, CNN: Cascade neural network

Table 3: STARE database fuzzy classifier

Fuzzy classifier	TP	TN	FP	FN
Normal	24	30	10	6
Moderate	26	20	20	14
Severe	20	14	10	6

TN: True negative, FP: False positive, TP: True positive, FN: False negative

Table 4: Accuracy, sensitivity, and specificity for different fundus images STARE dataset

Image	STARE dataset (normal)			Image	STARE dataset (abnormal)		
	Acc	Sen	Spe		Acc	Sen	Spe
1	97.5	90.11	96.83	1	99.55	99.94	93.84
2	97.72	90.77	97.90	2	97.54	99.95	91.44
3	97.66	90.83	95.84	3	97.57	99.92	92.55
4	97.73	90.96	97.29	4	97.60	99.89	92.80
5	97.69	90.80	96.83	5	97.69	99.80	93.83
6	97.64	90.85	95.16	6	97.64	99.85	92.16
7	97.73	90.76	97.32	7	97.73	99.76	92.32
8	97.06	90.73	98.11	8	97.06	99.73	92.11
9	97.72	90.77	97.74	9	97.72	99.77	93.74
10	97.73	90.76	98.36	10	97.73	99.76	93.36
Average	97.71	90.74	96.11	Average	99.71	99.963	93.86

Table 5: Accuracy, sensitivity, and specificity for different fundus images STARE dataset

Image	STARE dataset (normal)			Image	STARE dataset (abnormal)		
	Acc	Sen	Spe		Acc	Sen	Spe
1	99.80	96.69	98.69	1	99.85	100	95.84
2	99.77	96.72	99.54	2	99.54	99.95	91.44
3	99.77	96.72	99.29	3	99.57	99.83	92.55
4	99.73	96.76	98.34	4	99.60	99.79	92.80
5	99.70	96.79	97.13	5	99.69	99.80	93.83
6	99.70	96.79	97.20	6	99.64	99.83	92.16
7	99.63	96.86	94.13	7	99.73	99.76	92.32
8	99.70	96.79	97.18	8	99.06	99.73	92.11
9	99.80	96.69	99.30	9	99.72	99.77	93.74
10	99.65	96.84	95.51	10	99.75	99.75	93.55
Average	99.83	96.74	98.70	Average	99.88	100	95.86

Table 5 shows the accuracy, sensitivity, and specificity for different fundus images STARE dataset, the various methods are used to classify the data. From the data, many data are used, and 10 data are tabulated. The normal and abnormal are compared in this dataset. The proposed algorithm fuzzy classifier is used for severity measurement. By using the extracted features, Fuzzy classified the segmented image as the normal and abnormal and further the severity level of the abnormal image was classified as either high or low.

The performance of the system was evaluated. The result of the normal image CNN classification gives the accuracy of 97%, sensitivity of 90%, and specificity of 96%. The result of the normal image fuzzy classification gives the accuracy of 99%, sensitivity of 96%, and specificity of 98%.

CONCLUSION

The digital fundus images collected from the STARE database are preprocessed. The preprocessed image is segmented, and the blood vessels are separated from the lesions. Thus, the lesions were detected, and severity was measured from nondilated and low-contrast retinal digital images. CNN classifier is used for severity measurement. By using the extracted features, CNN classified the segmented image as the normal and abnormal and further the severity level of the abnormal image was classified as either high or low. The fuzzy classifier is incorporated to test the image; this is used to identify the lesion about the various categories such as high, medium, or low. Finally, we have concluded that CNN classifier is better than that of the fuzzy classifier. This is a useful method detects the symptoms faster and works effectively and also reduces the tedious work of the ophthalmologists.

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